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# Identifying Individuals using Multimodal Face Recognition Techniques

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**Abstract**

A biometric system which primarily based on the cues of unimodal biometric for individual identification is not always meet the desired results. The concept of multimodal biometrics for human Identification is an emerging trend. In this paper, we present state-of-the-art novel multimodal biometric system, for face recognition, which combines the similarity scores of the unimodal modalities such as appearance based and texture based techniques of face recognition, to cater the decisive results at the level of matching score. Formally, it includes the fusion of unimodal techniques to devise the multimodal models in four possible combinations such as (a) Eigenfaces and local binary pattern (LBP), (b) Fisherfaces and LBP, (c) organics' and augmented local binary pattern (A-LBP), and (d) Fisherfaces and A-LBP. The performance of the multimodal face recognition systems is tested on the publicly available face databases such as the AT & T-ORL and the Labeled Faces in the Wild (LFW) using a new Bray Curtis dissimilarity metric. The experimental results show a significant improvement in the performance of recognition accuracies of multimodal face recognition techniques.


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*Keywords:* Face recognition, multimodal biometric fusion, identification;Main text

## 1. Introduction


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Ever since the technology age started, companies and organizations paid high attention towards security because it is as a key to the gate in between, public and private territory that leads to the personal secret information, and they are implementing the secure identification systems to verify identity of individuals. Today password and Personal

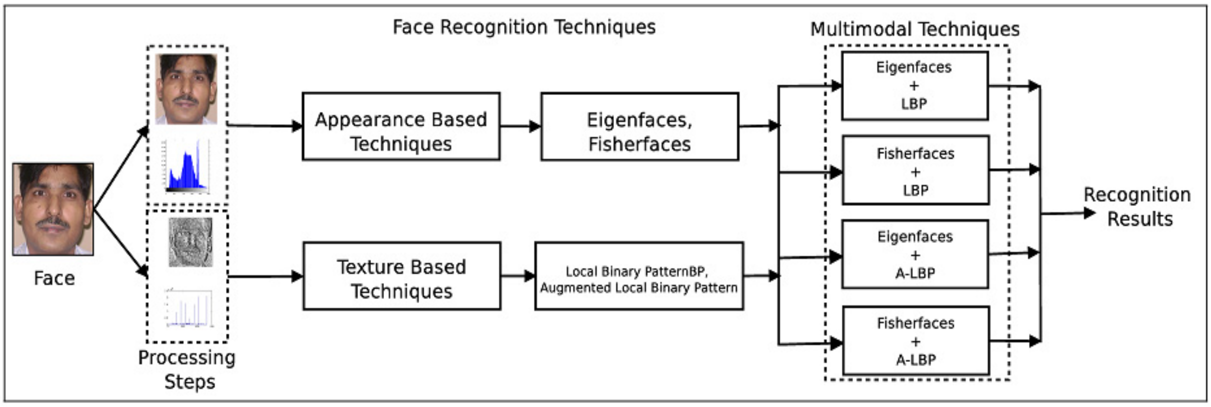


Fig. 1. Instances of proposed multimodal face recognition techniques.

Identification Number (PIN) is most commonly used to identify individuals are who they claim to be. However, these kinds of passwords require some sort of trust, such as trust from the administrator or from the machine that individuals accessing to. The password is only a secret code that eventually can be transferable, which means that there exists a high possibility a hacker could steal and attack. In addition, as we know it is too unsafe to have a single password for all accounts. Once an attacker got a hold of this password, it means one's life has pretty much taken over. To avoid that, individuals create different passwords for their accounts, which too difficult to remember from time-to-time. The biometric is an alternative solution to alleviate these problems. Biometric technologies are becoming the cornerstone of an extensive array of highly secure identification and personal verification solutions. As the level of security breaches and transaction fraud increases, the need for highly secure identification and personal verification technologies is becoming apparent. Biometric-based solutions are able to provide for confidential financial transactions and personal data privacy. The biometrics can be found useful in federal, state and local governments, military, and in commercial applications. Enterprise-wide network security infrastructures, government IDs, secure electronic banking, investing and other financial transactions, retail sales, law enforcement, and health and social services are already benefiting from these technologies.

Biometrics, refers a technology that is used to identify individuals based on the uniqueness of their body markers or their behavioral characteristics. Jain *et al.* Have identified number of factors that determine the suitability of a physical or a behavioral trait to be used in a biometric application. Presently, affluence of different biometric identifiers is being used in the literature, some of them are fingerprint, facial features, hand geometry, voice, iris, retina, vein patterns, palm print, DNA, keystroke rhythm, ear, odor, signature, gait/body recognition and ECG[1]. All these biometric identifiers have their own strengths and weakness in terms of the accuracy, user acceptance, and applicability. It is the requirements of an application domain which determine the choice of a specific biometric identifier. In order to enable a biometric system to operate effectively in different applications and environments, multimodal biometric systems are those that utilize more than one physiological or behavioral characteristic for enrollment, verification, or identification is preferred.

The work that has already been reported in the literature on multimodal biometric systems are: Dieckmann *et al.*, have proposed an abstract level fusion scheme: 2 out of 3 approach which combine face, lip motion, and voice based on the principle that a human uses multiple clues to identify a person[2]. Brunelli and Falavian, have proposed a measurement level scheme and a hybrid rank/measurement level scheme to combine the outputs of the sub-classifiers[3]. Brogan *et al.* And Maes *et al.*, have proposed to combine biometric data, e.g., voice with non-biometric data e.g., password[4, 5]. Kittler *et al*., have illustrated the efficiency of an amalgamation strategy which fuses multiple snapshots of a single biometric property using a Bayesian framework[6]. Hong and Jain have developed a multimodal identification system which combines two different biometrics that complement each other[7].

We design a multimodal biometric system which combines the cues from such as Eigenfaces and Local Binary Pattern (LBP), Fisherfaces and LBP, Eigenfaces and Augmented Local Binary Pattern (A-LBP), and Fisherfaces and A-LBP is based on the fact that they may be used in the law enforcement community. The remainder of this paper is organized as follows. The basics of appearance based and Feature based techniques are given in Section 2. In Section 3, the proposed multimodal fusions are presented. The performance of the multimodal face recognition systems on the new distance metric (BCD) is demonstrated in Section 4. Finally, the conclusion is drawn in Section 5.

## 2. Face Recognition Technique

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In literature, principally there are different types of face recognition techniques which are being used to identify individuals. Some of them are: (i) Appearance based techniques and (ii) Texture based techniques.

### *2.1. Appearance based statistical techniques*

The abundance of appearance based statistical techniques have been proposed in recent years, which are commonly used in identification by individuals through their facial images[8]. They generally differ in the type of projection and distance measure used. It includes some of the popular techniques, namely principal component analysis (PCA) [9], linear discriminant analysis (LDA) [10], fisherface[11, 12], independent component cnalysis (ICA) [13] and elastic bunch graph matching (EBGM) [14], etc.

### *2.2. Texture based techniques*

The plenty of texture based techniques have been proposed by the biometric researchers which are commonly used in identification by individuals through their facial images. Typically, they differ in the type of texture representation used. It includes the popular texture representation methods such as Local Binary Pattern (LBP) presented by Ojala *et al.* [15,16] and Augmented Local Binary Pattern (A-LBP) [17].

### *2.3. Multimodal Techniques*

A biometric system that combines more than one source of information for establishing human identity is called a multimodal biometric system. Combining the information cues from different biometric sources using an effective fusion scheme can significantly improve accuracy of a biometric system[18]. See the instances of proposed multimodal face recognition techniques in Fig. 1 The information fusion in multibiometrics can be done in different ways: fusion at the sensor level, feature extraction level, matching the score level and decision level. Sensor level fusion is rarely used as fusion at this level requires that the data obtained from the different biometric sensors must be compatible, which is seldom the case. Fusion at the feature extraction level is not always possible as the feature sets used by different biometric modalities may either be inaccessible or incompatible. Fusion at the decision level is too rigid as only a limited amount of information is available. Fusion at the matching score level is, therefore, preferred due to presence of sufficient information, content and the ease in accessing and combining match scores[19]. Each individual biometrics in our multimodal system have a different characteristic and a different matching scheme. Therefore, it is more reasonable to combine the multiple biometrics at the matching score level instead of at the sensor or feature extraction level.

## 3. Proposed Fusion of Face Recognition Techniques

Our intended approach is to fuse the tested unimodal face recognition techniques and to achieve a robust multimodal face recognition system. Formally, the possible combinations are condensed in fourfold: (a) Eigenfaces and LBP, (b) Fisherfaces and LBP, (c) organics' and A-LBP and (d) Fisherfaces and A-LBP. Where the individual similarity scores of the unimodal modalities are combined to cater the decisive results at the level of matching score accordingly. It can be formally formulated as, let A denote a given biometric system, and let $x^1$, $x^2$,....., $x^N$ denote the templates of the N users enrolled in A. Assume, that each enrolled user has only one template stored in the system. Hence the template for the Ith user, $x^i= [x^i_1, x^i_2]$, has two components, where $x^i_1$, $x^i_2$ are the templates for biometrics #01and #02 respectively. Let ($x^0$, I) denotes the biometric identifier and the identity claimed by a user. Again $x^0$ has two components, $x^0= x^0_1, x^0_2$, corresponding to the measurements of the two biometric identifiers. The claimed identity, I, either belongs to genuine class (T) or impostor class (F). The biometric system A matches $x^0$ against xi to determine which category, the claimed identity falls into, i.e.

$$I \in \begin{cases} \mathrm{T}, & \text{if } f(x^0, x^I) > th \\ \mathrm{F}, & \text{otherwise} \end{cases} \tag{1}$$

Where re f ($x^0$, $x^I$) is a function which measures the similarity between $x^0$ anxi$x^I$ andthisis a threshold.

Table 1. Face recognition accuracies (%) of fused techniques: (Eigenfaces and LBP), (Fisherfaces and LBP), (Eigenfaces and A-LBP) and (Fisherfaces and A-LBP) on different face databases using Bray Curtis Dissimilarity (BCD) metrics.

| Databases | Techniques | | Multimodal Fusion accuracy (%) |
|---|---|---|---|
| | Constrained environments #01 accuracy (%) | Unconstrained environments #02 accuracy (%) | |
| AT & T-ORL | Eigenfaces | LBP | Eigenfaces + LBP |
| | 95.45 | 94.92 | 99.81 |
| | Fisherfaces | LBP | Fisherfaces + LBP |
| | 97.50 | 94.92 | **99.87** |
| | Eigenfaces | A-LBP | Eigenfaces + A-LBP |
| | 95.45 | 95.00 | 99.84 |
| | Fisherfaces | A-LBP | Fisherfaces + A-LBP |
| | 97.50 | 95.00 | 99.84 |
| LFW | Eigenfaces | LBP | Eigenfaces + LBP |
| | 65.00 | 65.29 | 77.50 |
| | Fisherfaces | LBP | Fisherfaces + LBP |
| | 69.97 | 65.29 | **82.92** |
| | Eigenfaces | A-LBP | Eigenfaces + A-LBP |
| | 65.00 | 67.37 | 80.00 |
| | Fisherfaces | A-LBP | Fisherfaces + A-LBP |
| | 69.97 | 67.37 | 82.50 |

For a claimed identity I which can be in either T or F, the biometric system may determine whether I am in T or F. Therefore, there are a four possible outcomes: (i) a claimed identity in T is determined to be in T, (ii) a claimed identity in T is determined to be in F, (iii) a claimed identity in F is determined to be in F, and (iv) a claimed identity in F is determined to be in T, outcome (i) corresponds to a genuine user being accepted, outcome (ii) corresponds to a genuine user being rejected, outcome (iii) corresponds to an impostor being rejected, and outcome (iv) corresponds to an impostor being accepted, Obviously, outcomes (i) and (iii) are correct whereas outcomes (ii) and (iv) are incorrect. Ideally, a biometric system should make only correct decisions. In practice, due to large intra-class variations in the acquired digital representation of the biometric identifier, incorrect decisions are inevitable. Commonly, (i) false acceptance rate (FAR) and (ii) false reject rate (FRR) are used to characterized the performance of a biometric system. The false acceptance rate corresponds to the probability of outcome (iv) and the false reject rate is defined as the probability outcome (ii). The lower the values of the FAR and FRR, are more reliable is the decision made by the system. The FAR and FRR values of a given biometric system are determined by the inherent inter-class and intra-class variations of the identifier and the design of the system. The ROC curve is plotted between value of TAR (1-FRR) and FAR.

## 4. Experimental Results

The efficacy of the multimodal face recognition techniques are tested on the publicly available face databases such as AT & T-ORL[20] and Labeled Faces in the Wild[21] using Bray Curtis dissimilarity metric (BCD)[22]. These databases differ in the degree of variation in pose (p), illumination (i), expression (e) and eye glasses (eg) present in their facial images. The results of the multimodal biometric systems are shown in Table 1.

The performance of the proposed multimodal face biometric systems is analyzed using equal error rate, which is an error, where the likelihood of acceptance assumed the same value to the likelihood of rejection of people who should be correctly verified. The performance of the multimodal biometric systems is also confirmed by the receiver operating characteristic (ROC) curves. The ROC curve is a measure of classification performance that plots the true acceptance rate (TAR) against the false acceptance rate (FAR).

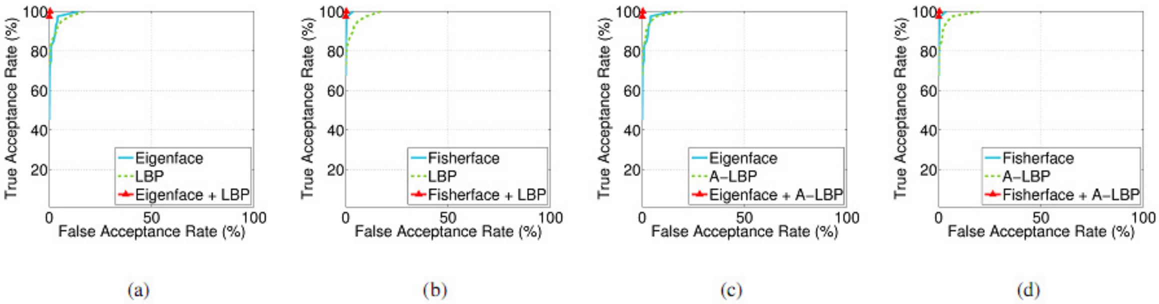


Fig. 2. ROC curves representing the performance of fused techniques using Bray Curtis dissimilarity metric on the AT & T-ORL face databases: (a) Eigenfaces and LBP, (b) Fisherfaces and LBP, (c) Eigenfaces and A-LBP, and (d) Fisherfaces and A-LBP.

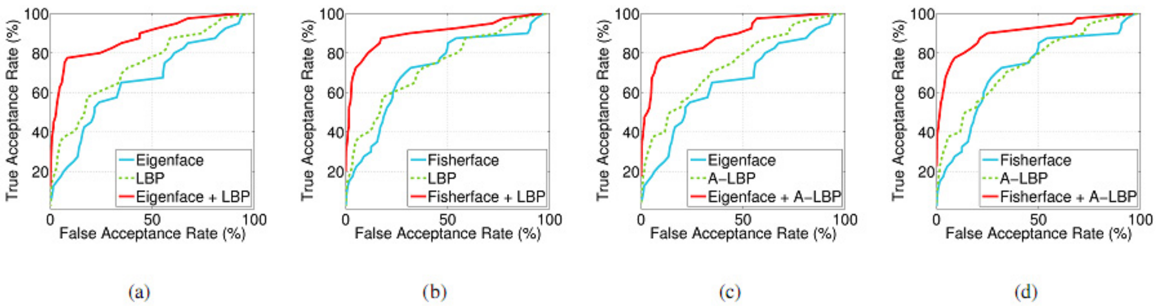


Fig. 3. ROC curves representing the performance of fused techniques using Bray Curtis dissimilarity metric on the Labeled Faces in the Wild (LFW) face databases: (a) Eigenfaces and LBP, (b) Fisherfaces and LBP, (c) Eigenfaces and A-LBP, and (d) Fisherfaces and A-LBP.

### *4.1. Recognition Results for AT & T-ORL Face Database*

The ROC curves for AT & T-ORL face database are plotted for different multimodal face recognition techniques using BCD metric and are shown in Fig. 2. The recognition result for the fusion of Eigenfaces and LBP techniques is shown in Fig. 2 (a). It reports the higher value of TAR of 99.81% at zero FAR. A similar trend is observed by all other fused modalities of face recognition techniques and reported the TAR of, 99.87% for the fusion of Fisherfaces and LBP techniques, 99.84% for the fusion of Eigenfaces and A-LBP techniques, and 99.84% for the fusion of

Fisherfaces and A-LBP techniques at zero value of FAR. The ROC curves of the fused modalities are respectively shown in Fig. 2(b), Fig. 2 (c) and Fig. 2 (d).

### *4.2. Recognition Results for LFW Face Database*

The ROC curves for LFW face database are plotted for different multimodal face recognition techniques using BCD metric and are shown in Fig. 3. The recognition result for the fusion of Eigenfaces and LBP techniques is shown in Fig. 3 (a). It reports the TAR value of 77.50% at 5% of FAR. For other fused modalities, the TAR vaues are found as, 82.92% for the fusion of Fisherfaces and LBP techniques, 80% for the fusion of Eigenfaces and A-LBP techniques, and 82.5% for the fusion of Fisherfaces and A-LBP techniques near to 5% of FAR. The ROC curves of the fused modalities are respectively shown in Fig. 3 (b), Fig. 3 (c) and Fig. 3 (d).

## 5. Conclusion

This paper has presented the approaches of multimodal face recognition techniques. We evaluated diffrent unimodal face recognition techniques namely Eigenfaces, Fisherfaces, LBP and A-LBP and the possible fusion of these techniques. In particular, the performance of fused techniques such as Eigenfaces and LBP, Fisherfaces and LBP, Eigenfaces and A-LBP, and Fisherfaces and A-LBP is evaluated on publicly available face databases using Bray Curtis dissimilarity metric. The recognition results obtained by the fused technique are found optimum in comparison to their unimodal techniques.

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